Final Project

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Contents

1 Variable

Pick one of the quantitative independent variables from the training data set (train.csv), and define that variable as X.

Pick SalePrice as the dependent variable, and define it as Y for the next analysis.

1.1 Variable Picked

> The variable we will set to X is LotArea, which is defined as the Lot size in square feet. I chose LotArea because an anecdotal assumption is that the larger the lot size is the higher the sale price. However, living in NYC, I know that tiny lots in very desirable places have sold for a high price so I believe there may be some interesting varability.

```
library(tidyverse)
train.df  <- as_tibble(read.csv(paste("https://raw.githubusercontent.com/",
                                      "ChristopheHunt/",
                                      "MSDA---Coursework/master",
                                      "/Data%20605/Final%20Project/train.csv",
                                      sep = "")))
```

```
sub.train.df <- train.df[, c("SalePrice", "LotArea")]
```

2 Probability

Calculate as a minimum the below probabilities a through c.

Assume the small letter "x" is estimated as the 4th quartile of the X variable, and the small letter "y" is estimated as the 2nd quartile of the Y variable. Interpret the meaning of all probabilities.

```
prob.x <- list(qrt = as.numeric(quantile(sub.train.df$LotArea)[4]))

prob.y <- list(qrt = as.numeric(quantile(sub.train.df$SalePrice)[2]))
```

```
prob.y.x <- sub.train.df %>% mutate(greaterLotArea = ifelse(LotArea >= prob.x$qrt, 1, 0),
                                     lesserLotArea = ifelse(LotArea < prob.x$qrt, 1, 0),
                                     greaterSalePrice = ifelse(SalePrice >= prob.y$qrt,1, 0),
                                     lesserSalePrice = ifelse(SalePrice < prob.y$qrt,1, 0))
```

2.1 a. $P(X > x|Y > y)$

```
a <- (sum(ifelse(prob.y.x$greaterLotArea == 1 &
                   prob.y.x$greaterSalePrice == 1, 1, 0))
      / nrow(prob.y.x)) / ((sum(prob.y.x$greaterLotArea) / nrow(prob.y.x)))
a
```

```
## [1] 0.9369863
```

2.2 b. $P(X > x, Y > y)$

```
b <- sum(ifelse(prob.y.x$greaterLotArea == 1 &
                  prob.y.x$greaterSalePrice == 1, 1, 0))/nrow(prob.y.x)
b
```

```
## [1] 0.2342466
```

2.3 c. $P(X < x|Y > y)$

```
c <- (sum(ifelse(prob.y.x$lesserLotArea == 1 &
                   prob.y.x$greaterSalePrice == 1, 1, 0))
      / nrow(prob.y.x)) / ((sum(prob.y.x$lesserLotArea) / nrow(prob.y.x)))
c
```

```
## [1] 0.6876712
```

Does splitting the training data in this fashion make them independent?

In other words, does $P(X|Y) = P(X)P(Y)$?

> I am understanding this to mean does the probability of X>x given Y>y, which was answered for in part a. above, equal the probability of X>x mutiplied by Y>y

2.4 Mathematical Check for $P(X|Y) = P(X)P(Y)$

```
X <- sum(prob.y.x$greaterLotArea)/ nrow(prob.y.x)
Y <- sum(prob.y.x$greaterSalePrice) / nrow(prob.y.x)
X * Y
```

```
## [1] 0.1875
```

```
a == (X * Y)
```

```
## [1] FALSE
```

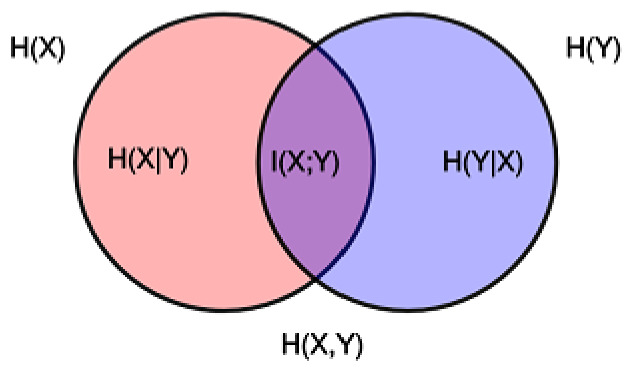
2.5 Chi Square test for association.

```r
prob.table <- as.data.frame(rbind(cbind(sum(prob.y.x$lesserLotArea),
                                        sum(prob.y.x$greaterLotArea)),
                                  cbind(sum(prob.y.x$lesserSalePrice),
                                        sum(prob.y.x$greaterSalePrice))))
chisq.test(prob.table)
```

```
##
##  Pearson's Chi-squared test with Yates' continuity correction
##
## data:  prob.table
## X-squared = 728, df = 1, p-value < 2.2e-16
```

We see that the p-value is quite low, lower than the assumptive .05, so we therefore reject the null hypothesis that the values are independent of each other.

The below venn diagram from Wikipedia may provide a clearer understanding of the differences in these measures:



[1]

[1] By KonradVoelkel (Own work) [Public domain], via Wikimedia Commons

3 Descriptive and Inferential Statistics.

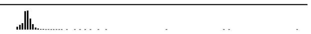
3.1 Univariate descriptive statistics and plots

3.1.1 Lot Area

```r
description <- describe(sub.train.df["LotArea"],descript = "LotArea")
latex(description, file = '')
```

LotArea
1 Variables 1460 Observations

LotArea



n	missing	distinct	Info	Mean	Gmd	.05	.10	.25	.50	.75	.90	.95
1460	0	1073	1	10517	5718	3312	5000	7554	9478	11602	14382	17401

`lowest : 1300 1477 1491 1526 1533, highest: 70761 115149 159000 164660 215245`

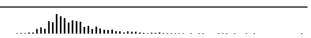
The histogram in the upper right corner of the table shows a right skewed distribution, which is not surprising since houses in cities would likely have similar lot areas versus instances of varied rural large lot areas.

3.1.2 Sale Price

```r
description <- describe(sub.train.df["SalePrice"], descript = "SalePrice")
latex(description, file = '')
```

SalePrice
1 Variables 1460 Observations

SalePrice



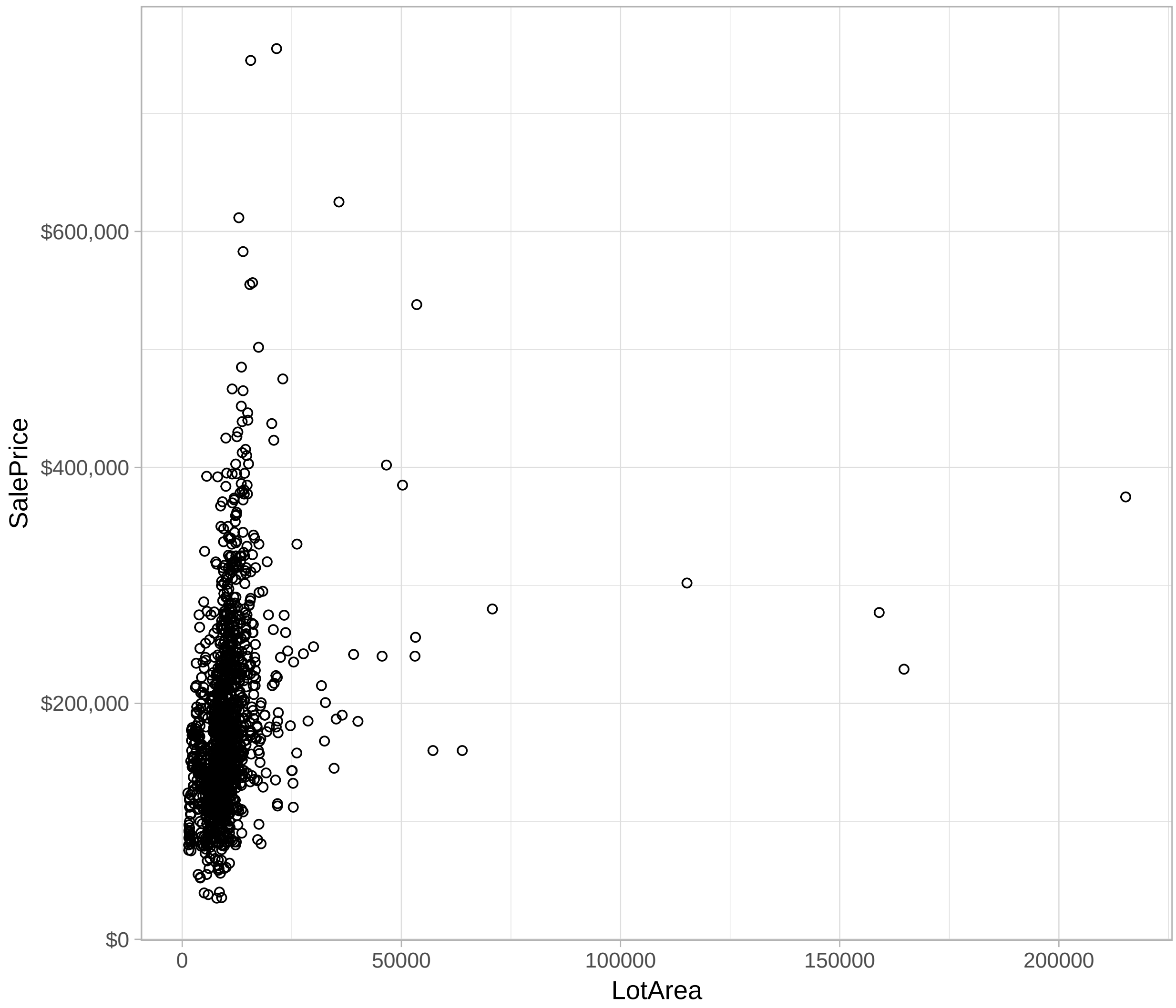
n	missing	distinct	Info	Mean	Gmd	.05	.10	.25	.50	.75	.90	.95
1460	0	663	1	180921	81086	88000	106475	129975	163000	214000	278000	326100

`lowest : 34900 35311 37900 39300 40000, highest: 582933 611657 625000 745000 755000`

As we can see from the histogram the shape of the data is near normal. It is interesting to visualize that lot area does not follow the same shape, this would hold with our original assumption that where the house is located has more impact than the size of the lot area.

3.2 Scatterplot of X and Y

```
ggplot(sub.train.df, aes(x = LotArea, y = SalePrice)) +
    geom_point(shape=1) +
    theme_light() +
    scale_y_continuous(labels = dollar)
```



I expected this type of scatter plot based on my anecdotal assumption of cities vs rural areas. I would think that the differences within the city limits have high variance in price but less variation in lot area. My assumption is that the large lot areas at the mid sale price is likely in a rural area.

3.3 Box-Cox transformations.

I am using the `BoxCox.lambda` function from the `forecast` package to determine the necessary transformations for the two variables.

```
library(forecast)
library(knitr)
l1 <- BoxCox.lambda(as.numeric(sub.train.df$SalePrice))
l2 <- BoxCox.lambda(as.numeric(sub.train.df$LotArea))

lamdas <- c(l1, l2)
Variables <- c("SalePrice", "LotArea")
dfBoxCox <- as.data.frame(cbind(round(as.numeric(lamdas),4), Variables))
colnames(dfBoxCox) <- c("$\\lambda$", "Variables")
kable(dfBoxCox, align = c("c", "c"))
```

λ	Variables
-0.3308	SalePrice
-0.1268	LotArea

Common Box-Cox Transformations[2] [3]

λ	Y'
-0.5	$Y^{-0.5} = \frac{1}{\sqrt{(Y)}}$
0	$\log(Y)$
.25	$\sqrt[4]{Y}$

***

Lambda values were truncated to the nearest tenth
that match a common transformation as per the below table.

variable	variable transformation
SalePrice	$SalePrice^{-0.5}$
LotArea	$log(LotArea)$

[2] Osborne, Jason W. "Improving your data transformations: Applying the Box-Cox transformation." Practical Assessment, Research & Evaluation 15.12 (2010): 1-9.

[3] By Understanding Both the Concept of Transformation and the Box-Cox Method, Practitioners Will Be Better Prepared to Work with Non-normal Data. . "Making Data Normal Using Box-Cox Power Transformation." ISixSigma. N.p., n.d. Web. 29 Oct. 2016.

3.4 Correlation Analysis

3.4.1 Correlation analysis and interpetation

```
sub.train.df.trans <- sub.train.df %>%
                      mutate(SalePrice = SalePrice^(-.5),
                             LotArea = log(LotArea))

sub.train.cor <- cor.test(sub.train.df.trans$SalePrice,
                          sub.train.df.trans$LotArea,
                          method = "pearson", conf.level = .99)
sub.train.cor
```

```
##
##  Pearson's product-moment correlation
##
## data:  sub.train.df.trans$SalePrice and sub.train.df.trans$LotArea
## t = -15.968, df = 1458, p-value < 2.2e-16
## alternative hypothesis: true correlation is not equal to 0
## 99 percent confidence interval:
##  -0.4417063 -0.3269282
## sample estimates:
##        cor
## -0.3858091
```

The p-value of the correlation test is 2.2e-16 which is less than the significance level of alpha at .05. We are using the standard alpha as there is no indication another any other value for alpha should be used. We can therefore say that the log of lot size and sale price raised to the -.5 power are significantly correlated with a negative correlation coefficient of -0.386.

3.4.2 Null hypothesis test at a 99% confidence interval.

The correlation test has specifically done that for us and we can safely reject the null hypothesis as we see that our 99% confidence interval exists at the values (-0.441, -0.327) with a p-value < 2.2e-16.

3.4.3 Analysis Discussion

This means two possible things could have occured, there is no correlation and this data set is pulled from an unusual set of house sales. Or, more likely with the values obtained, our assumption of 0 correlation is incorect and we have obtained a very typical data set and must reject the null hypothesis because correlation does exist.

4 Linear Algebra and Correlation.

4.1 Correlation Matrix

```
A <- cor(sub.train.df.trans)
kable(A)
```

	SalePrice	LotArea
SalePrice	1.0000000	-0.3858091
LotArea	-0.3858091	1.0000000

4.2 Inverted correlation matrix (percision matrix)

```
B <- solve(A)
kable(B)
```

	SalePrice	LotArea
SalePrice	1.1748792	0.4532792
LotArea	0.4532792	1.1748792

4.3 Multiply the correlation matrix by the precision matrix, and then multiply the precision matrix by the correlation matrix.

```
corr.by.pre.M <- A %*% B
kable(corr.by.pre.M)
```

	SalePrice	LotArea
SalePrice	1	0
LotArea	0	1

```
pre.by.corr.M <- B %*% A
kable(pre.by.corr.M)
```

	SalePrice	LotArea
SalePrice	1	0
LotArea	0	1

5 Calculus-Based Probability & Statistics

5.1 Location Shift

Many times, it makes sense to fit a closed form distribution to data. For your non-transformed independent variable, location shift it so that the minimum value is above zero.

```
min(sub.train.df$LotArea)
```

[1] 1300

> For the independent variable chosen, there are no zero values observed. This makes sense as we would expect the lot area to have some value and I would expect it to never be unobserved (an assumption that at least estimates would be used without a true figure).
>
> However, if a shift was required something like the below could be used.

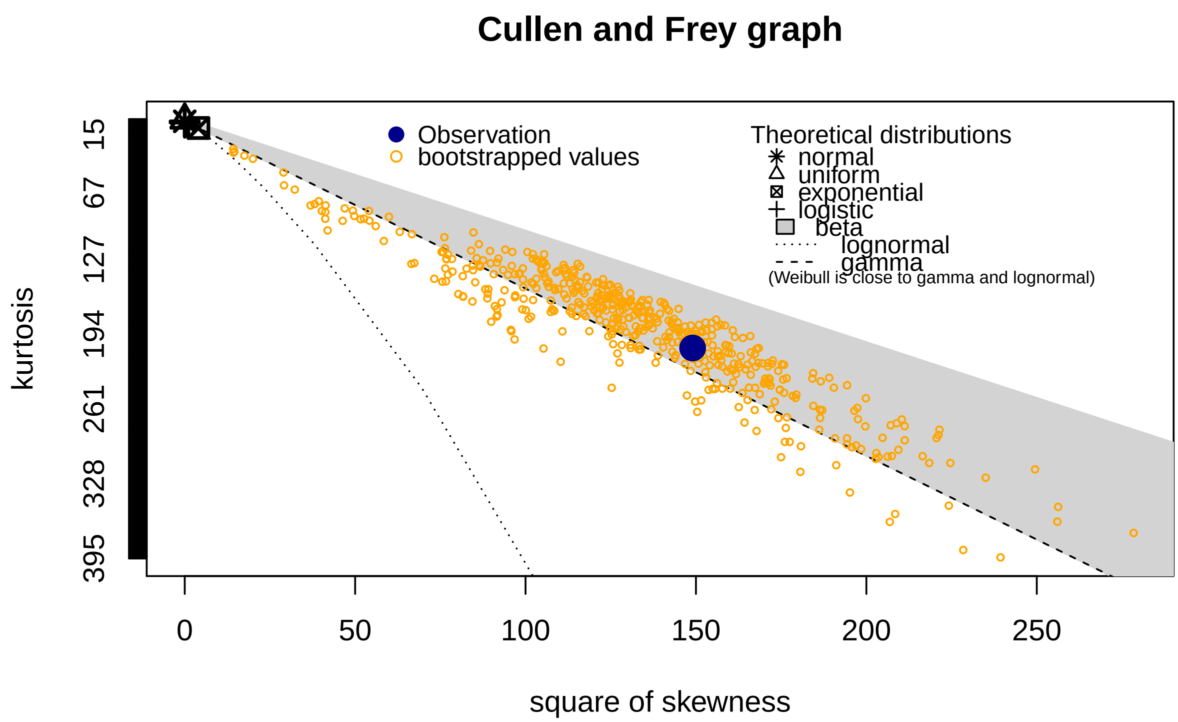
```
shift <- sub.train.df$LotArea + 1
```

5.2 Mass and `fitdistr`

Then load the MASS package and run fitdistr to fit a density function of your choice. (See https://stat.ethz.ch/R-manual/R-devel/library/MASS/html/fitdistr.html).

5.2.1 Best fit distribution.

```
library(fitdistrplus)
descdist(sub.train.df$LotArea, discrete=FALSE, boot=500)
```




```
## summary statistics
## ------
## min:  1300   max:  215245
## median:  9478.5
## mean:  10516.83
## estimated sd:  9981.265
## estimated skewness:  12.20769
## estimated kurtosis:  206.2433
```

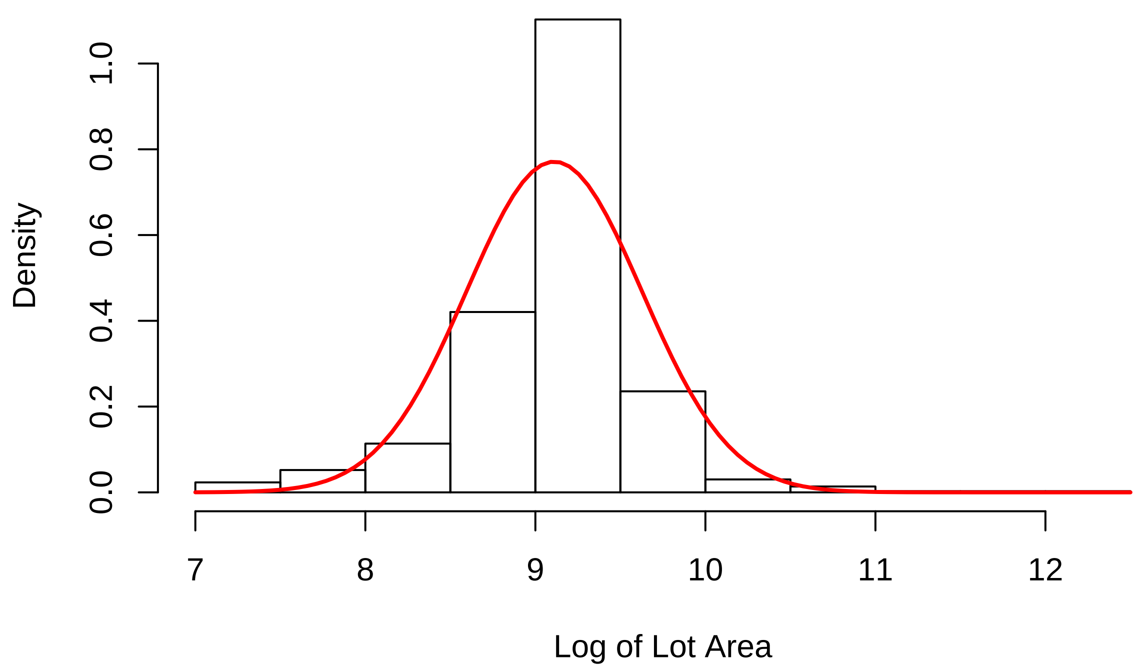
5.3 Fitting Distribution

There were too many issues in attempting to fit the `beta` distribution so the next best theoretical distribution was used - `log normal`.

```
library(MASS)
fit.log <- fitdistr(sub.train.df$LotArea, densfun = "log-normal")
fit.log
```

```
##      meanlog        sdlog
##   9.110838240   0.517270830
##  (0.013537596) (0.009572526)
```

```
hist(log(sub.train.df$LotArea), prob=TRUE, xlab = "Log of Lot Area", main = "")
curve(dnorm(x, fit.log$estimate[1], fit.log$estimate[2]), col="red", lwd=2, add=T)
```



Our density plot indicates that the log normal distribution fits quite well.

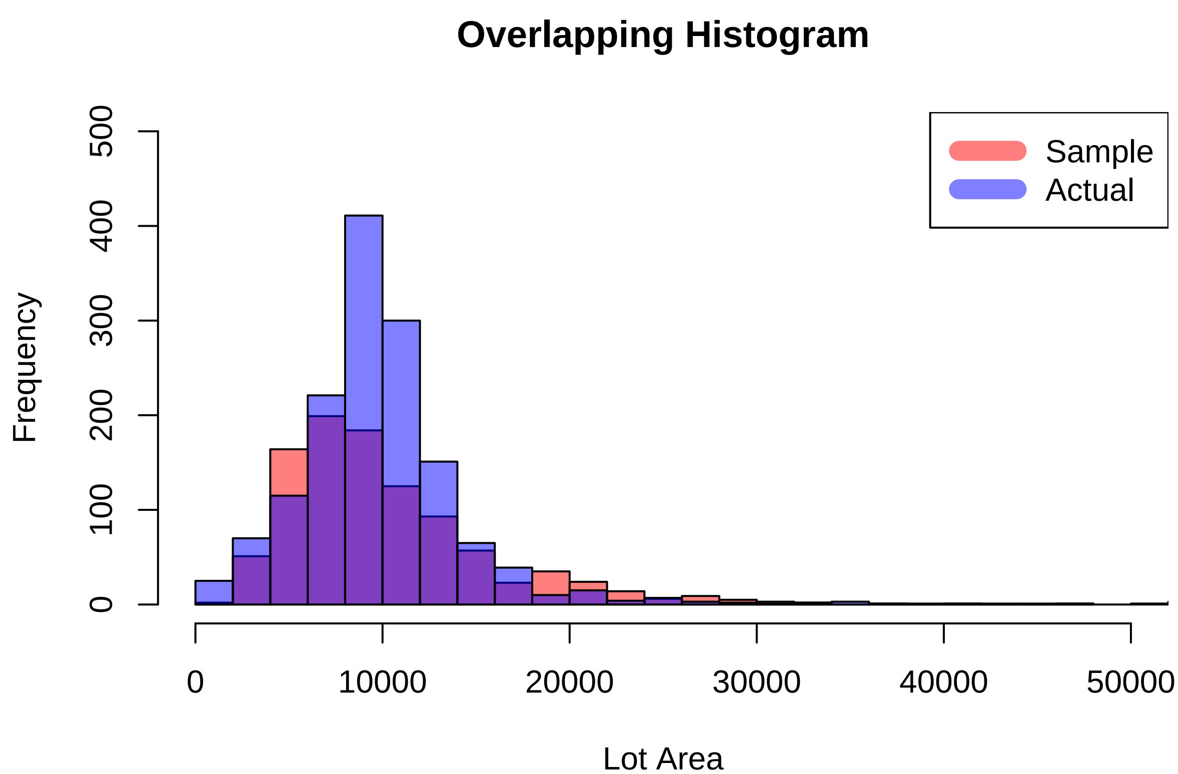
5.4 Sampling

Find the optimal value of the parameters for this distribution, and then take 1000 samples from this distribution (e.g., rexp(1000) for an exponential).

```
set.seed(1234)
sample <- rlnorm(1000, meanlog = fit.log$estimate[1], sdlog = fit.log$estimate[2])
```

Plot a histogram and compare it with a histogram of your non-transformed original variable.

```
hist(sample, pch = 20, breaks = 25, col = rgb(1,0,0,0.5),
     xlim = c(0,50000), ylim = c(0,500),
     main = 'Overlapping Histogram', xlab = 'Lot Area')
hist(sub.train.df$LotArea, pch = 20, breaks = 100,
     col = rgb(0,0,1,0.5), add = T)
#https://www.r-bloggers.com/overlapping-histogram-in-r/
legend("topright", c("Sample", "Actual"), col=c(rgb(1,0,0,0.5), rgb(0,0,1,0.5)), lwd=10)
```



It is clear that the distributions are very similar. Plotting them together gives a clear visual of how similar the distributions are and note that x has been limited to not extend to extreme values.

6 Modeling

6.1 Regression model.

6.1.1 Variable Exploration

```
description <- describe(train.df %>% dplyr::select(-Id, -SalePrice), descript = "Training Data Set")
latex(description, file = '')
```

Training Data Set
79 Variables 1460 Observations

MSSubClass

n	missing	distinct	Info	Mean	Gmd	.05	.10	.25	.50	.75	.90	.95
1460	0	15	0.94	56.9	43.19	20	20	20	50	70	120	160

Value	20	30	40	45	50	60	70	75	80	85	90	120	160	180
Frequency	536	69	4	12	144	299	60	16	58	20	52	87	63	10
Proportion	0.367	0.047	0.003	0.008	0.099	0.205	0.041	0.011	0.040	0.014	0.036	0.060	0.043	0.007

Value	190
Frequency	30
Proportion	0.021

MSZoning

n	missing	distinct
1460	0	5

Value	C (all)	FV	RH	RL	RM
Frequency	10	65	16	1151	218
Proportion	0.007	0.045	0.011	0.788	0.149

LotFrontage

n	missing	distinct	Info	Mean	Gmd	.05	.10	.25	.50	.75	.90	.95
1201	259	110	0.998	70.05	24.61	34	44	59	69	80	96	107

```
lowest :  21  24  30  32  33, highest: 160 168 174 182 313
```

LotArea

n	missing	distinct	Info	Mean	Gmd	.05	.10	.25	.50	.75	.90	.95
1460	0	1073	1	10517	5718	3312	5000	7554	9478	11602	14382	17401

```
lowest :    1300    1477    1491    1526    1533, highest:  70761 115149 159000 164660 215245
```

Street

n	missing	distinct
1460	0	2

Value	Grvl	Pave
Frequency	6	1454
Proportion	0.004	0.996

Alley

n	missing	distinct
91	1369	2

Value	Grvl	Pave
Frequency	50	41
Proportion	0.549	0.451

LotShape

n	missing	distinct
1460	0	4

Value	IR1	IR2	IR3	Reg
Frequency	484	41	10	925
Proportion	0.332	0.028	0.007	0.634

LandContour

n	missing	distinct
1460	0	4

Value	Bnk	HLS	Low	Lvl
Frequency	63	50	36	1311
Proportion	0.043	0.034	0.025	0.898

Utilities

n	missing	distinct
1460	0	2

Value	AllPub	NoSeWa
Frequency	1459	1
Proportion	0.999	0.001

LotConfig

n	missing	distinct
1460	0	5

Value	Corner	CulDSac	FR2	FR3	Inside
Frequency	263	94	47	4	1052
Proportion	0.180	0.064	0.032	0.003	0.721

LandSlope

n	missing	distinct
1460	0	3

Value	Gtl	Mod	Sev
Frequency	1382	65	13
Proportion	0.947	0.045	0.009

Neighborhood

n	missing	distinct
1460	0	25

lowest : Blmngtn Blueste BrDale BrkSide ClearCr, highest: Somerst StoneBr SWISU Timber Veenker

Condition1

n	missing	distinct
1460	0	9

Value	Artery	Feedr	Norm	PosA	PosN	RRAe	RRAn	RRNe	RRNn
Frequency	48	81	1260	8	19	11	26	2	5
Proportion	0.033	0.055	0.863	0.005	0.013	0.008	0.018	0.001	0.003

Condition2

n	missing	distinct
1460	0	8

Value	Artery	Feedr	Norm	PosA	PosN	RRAe	RRAn	RRNn
Frequency	2	6	1445	1	2	1	1	2
Proportion	0.001	0.004	0.990	0.001	0.001	0.001	0.001	0.001

BldgType

n	missing	distinct
1460	0	5

Value	1Fam	2fmCon	Duplex	Twnhs	TwnhsE
Frequency	1220	31	52	43	114
Proportion	0.836	0.021	0.036	0.029	0.078

HouseStyle

n	missing	distinct
1460	0	8

Value	1.5Fin	1.5Unf	1Story	2.5Fin	2.5Unf	2Story	SFoyer	SLvl
Frequency	154	14	726	8	11	445	37	65
Proportion	0.105	0.010	0.497	0.005	0.008	0.305	0.025	0.045

OverallQual

n	missing	distinct	Info	Mean	Gmd	.05	.10	.25	.50	.75	.90	.95
1460	0	10	0.951	6.099	1.522	4	5	5	6	7	8	8

Value	1	2	3	4	5	6	7	8	9	10
Frequency	2	3	20	116	397	374	319	168	43	18
Proportion	0.001	0.002	0.014	0.079	0.272	0.256	0.218	0.115	0.029	0.012

OverallCond

n	missing	distinct	Info	Mean	Gmd
1460	0	9	0.814	5.575	1.111

Value	1	2	3	4	5	6	7	8	9
Frequency	1	5	25	57	821	252	205	72	22
Proportion	0.001	0.003	0.017	0.039	0.562	0.173	0.140	0.049	0.015

YearBuilt

n	missing	distinct	Info	Mean	Gmd	.05	.10	.25	.50	.75	.90	.95
1460	0	112	1	1971	33.88	1916	1925	1954	1973	2000	2006	2007

lowest : 1872 1875 1880 1882 1885, highest: 2006 2007 2008 2009 2010

YearRemodAdd

n	missing	distinct	Info	Mean	Gmd	.05	.10	.25	.50	.75	.90	.95
1460	0	61	0.997	1985	23.05	1950	1950	1967	1994	2004	2006	2007

lowest : 1950 1951 1952 1953 1954, highest: 2006 2007 2008 2009 2010

RoofStyle

n	missing	distinct
1460	0	6

Value	Flat	Gable	Gambrel	Hip	Mansard	Shed
Frequency	13	1141	11	286	7	2
Proportion	0.009	0.782	0.008	0.196	0.005	0.001

RoofMatl

n	missing	distinct
1460	0	8

Value	ClyTile	CompShg	Membran	Metal	Roll	Tar&Grv	WdShake	WdShngl
Frequency	1	1434	1	1	1	11	5	6
Proportion	0.001	0.982	0.001	0.001	0.001	0.008	0.003	0.004

Exterior1st

n	missing	distinct
1460	0	15

Value	AsbShng	AsphShn	BrkComm	BrkFace	CBlock	CemntBd	HdBoard	ImStucc	MetalSd	Plywood
Frequency	20	1	2	50	1	61	222	1	220	108
Proportion	0.014	0.001	0.001	0.034	0.001	0.042	0.152	0.001	0.151	0.074

Value	Stone	Stucco	VinylSd	Wd Sdng	WdShing
Frequency	2	25	515	206	26
Proportion	0.001	0.017	0.353	0.141	0.018

Exterior2nd

n	missing	distinct
1460	0	16

Value	AsbShng	AsphShn	Brk Cmn	BrkFace	CBlock	CmentBd	HdBoard	ImStucc	MetalSd	Other
Frequency	20	3	7	25	1	60	207	10	214	1
Proportion	0.014	0.002	0.005	0.017	0.001	0.041	0.142	0.007	0.147	0.001

Value	Plywood	Stone	Stucco	VinylSd	Wd Sdng	Wd Shng
Frequency	142	5	26	504	197	38
Proportion	0.097	0.003	0.018	0.345	0.135	0.026

MasVnrType

n	missing	distinct
1452	8	4

Value	BrkCmn	BrkFace	None	Stone
Frequency	15	445	864	128
Proportion	0.010	0.306	0.595	0.088

MasVnrArea

n	missing	distinct	Info	Mean	Gmd	.05	.10	.25	.50	.75	.90	.95
1452	8	327	0.791	103.7	156.9	0	0	0	0	166	335	456

lowest : 0 1 11 14 16, highest: 1115 1129 1170 1378 1600

ExterQual

n	missing	distinct
1460	0	4

Value	Ex	Fa	Gd	TA
Frequency	52	14	488	906
Proportion	0.036	0.010	0.334	0.621

ExterCond

n	missing	distinct
1460	0	5

Value	Ex	Fa	Gd	Po	TA
Frequency	3	28	146	1	1282
Proportion	0.002	0.019	0.100	0.001	0.878

Foundation

n	missing	distinct
1460	0	6

Value	BrkTil	CBlock	PConc	Slab	Stone	Wood
Frequency	146	634	647	24	6	3
Proportion	0.100	0.434	0.443	0.016	0.004	0.002

BsmtQual

n	missing	distinct
1423	37	4

Value	Ex	Fa	Gd	TA
Frequency	121	35	618	649
Proportion	0.085	0.025	0.434	0.456

BsmtCond

n	missing	distinct
1423	37	4

Value	Fa	Gd	Po	TA
Frequency	45	65	2	1311
Proportion	0.032	0.046	0.001	0.921

BsmtExposure

n	missing	distinct
1422	38	4

Value	Av	Gd	Mn	No
Frequency	221	134	114	953
Proportion	0.155	0.094	0.080	0.670

BsmtFinType1

n	missing	distinct
1423	37	6

Value	ALQ	BLQ	GLQ	LwQ	Rec	Unf
Frequency	220	148	418	74	133	430
Proportion	0.155	0.104	0.294	0.052	0.093	0.302

BsmtFinSF1

n	missing	distinct	Info	Mean	Gmd	.05	.10	.25	.50	.75	.90	.95
1460	0	637	0.967	443.6	484.5	0.0	0.0	0.0	383.5	712.2	1065.5	1274.0

```
lowest :    0    2   16   20   24, highest: 1904 2096 2188 2260 5644
```

BsmtFinType2

n	missing	distinct
1422	38	6

Value	ALQ	BLQ	GLQ	LwQ	Rec	Unf
Frequency	19	33	14	46	54	1256
Proportion	0.013	0.023	0.010	0.032	0.038	0.883

BsmtFinSF2

n	missing	distinct	Info	Mean	Gmd	.05	.10	.25	.50	.75	.90	.95
1460	0	144	0.305	46.55	86.58	0.0	0.0	0.0	0.0	0.0	117.2	396.2

```
lowest :    0   28   32   35   40, highest: 1080 1085 1120 1127 1474
```

BsmtUnfSF

n	missing	distinct	Info	Mean	Gmd	.05	.10	.25	.50	.75	.90	.95
1460	0	780	0.999	567.2	486.6	0.0	74.9	223.0	477.5	808.0	1232.0	1468.0

```
lowest :    0   14   15   23   26, highest: 2042 2046 2121 2153 2336
```

TotalBsmtSF

n	missing	distinct	Info	Mean	Gmd	.05	.10	.25	.50	.75	.90	.95
1460	0	721	1	1057	459.5	519.3	636.9	795.8	991.5	1298.2	1602.2	1753.0

```
lowest :    0  105  190  264  270, highest: 3094 3138 3200 3206 6110
```

Heating

n	missing	distinct
1460	0	6

Value	Floor	GasA	GasW	Grav	OthW	Wall
Frequency	1	1428	18	7	2	4
Proportion	0.001	0.978	0.012	0.005	0.001	0.003

HeatingQC

n	missing	distinct
1460	0	5

Value	Ex	Fa	Gd	Po	TA
Frequency	741	49	241	1	428
Proportion	0.508	0.034	0.165	0.001	0.293

CentralAir

n	missing	distinct
1460	0	2

Value	N	Y
Frequency	95	1365
Proportion	0.065	0.935

Electrical

n	missing	distinct
1459	1	5

Value	FuseA	FuseF	FuseP	Mix	SBrkr
Frequency	94	27	3	1	1334
Proportion	0.064	0.019	0.002	0.001	0.914

X1stFlrSF

n	missing	distinct	Info	Mean	Gmd	.05	.10	.25	.50	.75	.90	.95
1460	0	753	1	1163	416.4	673.0	756.9	882.0	1087.0	1391.2	1680.0	1831.2

lowest : 334 372 438 480 483, highest: 2633 2898 3138 3228 4692

X2ndFlrSF

n	missing	distinct	Info	Mean	Gmd	.05	.10	.25	.50	.75	.90	.95
1460	0	417	0.817	347	450.2	0.0	0.0	0.0	0.0	728.0	954.2	1141.0

lowest : 0 110 167 192 208, highest: 1611 1796 1818 1872 2065

LowQualFinSF

n	missing	distinct	Info	Mean	Gmd	.05	.10	.25	.50	.75	.90	.95
1460	0	24	0.052	5.845	11.55	0	0	0	0	0	0	0

lowest : 0 53 80 120 144, highest: 513 514 515 528 572

GrLivArea

n	missing	distinct	Info	Mean	Gmd	.05	.10	.25	.50	.75	.90	.95
1460	0	861	1	1515	563.1	848	912	1130	1464	1777	2158	2466

lowest : 334 438 480 520 605, highest: 3627 4316 4476 4676 5642

BsmtFullBath

n	missing	distinct	Info	Mean	Gmd
1460	0	4	0.733	0.4253	0.5085

Value	0	1	2	3
Frequency	856	588	15	1
Proportion	0.586	0.403	0.010	0.001

BsmtHalfBath

n	missing	distinct	Info	Mean	Gmd
1460	0	3	0.159	0.05753	0.1088

Value	0	1	2
Frequency	1378	80	2
Proportion	0.944	0.055	0.001

FullBath

n	missing	distinct	Info	Mean	Gmd
1460	0	4	0.766	1.565	0.5521

Value	0	1	2	3
Frequency	9	650	768	33
Proportion	0.006	0.445	0.526	0.023

HalfBath

n	missing	distinct	Info	Mean	Gmd
1460	0	3	0.706	0.3829	0.4852

Value	0	1	2
Frequency	913	535	12
Proportion	0.625	0.366	0.008

BedroomAbvGr

n	missing	distinct	Info	Mean	Gmd
1460	0	8	0.815	2.866	0.818

Value	0	1	2	3	4	5	6	8
Frequency	6	50	358	804	213	21	7	1
Proportion	0.004	0.034	0.245	0.551	0.146	0.014	0.005	0.001

KitchenAbvGr

n	missing	distinct	Info	Mean	Gmd
1460	0	4	0.133	1.047	0.09174

Value	0	1	2	3
Frequency	1	1392	65	2
Proportion	0.001	0.953	0.045	0.001

KitchenQual

n	missing	distinct
1460	0	4

Value	Ex	Fa	Gd	TA
Frequency	100	39	586	735
Proportion	0.068	0.027	0.401	0.503

TotRmsAbvGrd

n	missing	distinct	Info	Mean	Gmd	.05	.10	.25	.50	.75	.90	.95
1460	0	12	0.958	6.518	1.762	4	5	5	6	7	9	10

Value	2	3	4	5	6	7	8	9	10	11	12	14
Frequency	1	17	97	275	402	329	187	75	47	18	11	1
Proportion	0.001	0.012	0.066	0.188	0.275	0.225	0.128	0.051	0.032	0.012	0.008	0.001

Functional

n	missing	distinct
1460	0	7

Value	Maj1	Maj2	Min1	Min2	Mod	Sev	Typ
Frequency	14	5	31	34	15	1	1360
Proportion	0.010	0.003	0.021	0.023	0.010	0.001	0.932

Fireplaces

n	missing	distinct	Info	Mean	Gmd
1460	0	4	0.806	0.613	0.6566

Value	0	1	2	3
Frequency	690	650	115	5
Proportion	0.473	0.445	0.079	0.003

FireplaceQu

n	missing	distinct
770	690	5

Value	Ex	Fa	Gd	Po	TA
Frequency	24	33	380	20	313
Proportion	0.031	0.043	0.494	0.026	0.406

GarageType

n	missing	distinct
1379	81	6

Value	2Types	Attchd	Basment	BuiltIn	CarPort	Detchd
Frequency	6	870	19	88	9	387
Proportion	0.004	0.631	0.014	0.064	0.007	0.281

GarageYrBlt

n	missing	distinct	Info	Mean	Gmd	.05	.10	.25	.50	.75	.90	.95
1379	81	97	1	1979	27.63	1930	1945	1961	1980	2002	2006	2007

lowest : 1900 1906 1908 1910 1914, highest: 2006 2007 2008 2009 2010

GarageFinish

n	missing	distinct
1379	81	3

Value	Fin	RFn	Unf
Frequency	352	422	605
Proportion	0.255	0.306	0.439

GarageCars

n	missing	distinct	Info	Mean	Gmd
1460	0	5	0.802	1.767	0.7609

Value	0	1	2	3	4
Frequency	81	369	824	181	5
Proportion	0.055	0.253	0.564	0.124	0.003

GarageArea

n	missing	distinct	Info	Mean	Gmd	.05	.10	.25	.50	.75	.90	.95
1460	0	441	1	473	234.9	0.0	240.0	334.5	480.0	576.0	757.1	850.1

lowest : 0 160 164 180 186, highest: 1220 1248 1356 1390 1418

GarageQual

n	missing	distinct
1379	81	5

Value	Ex	Fa	Gd	Po	TA
Frequency	3	48	14	3	1311
Proportion	0.002	0.035	0.010	0.002	0.951

GarageCond

n	missing	distinct
1379	81	5

Value	Ex	Fa	Gd	Po	TA
Frequency	2	35	9	7	1326
Proportion	0.001	0.025	0.007	0.005	0.962

PavedDrive

n	missing	distinct
1460	0	3

Value	N	P	Y
Frequency	90	30	1340
Proportion	0.062	0.021	0.918

WoodDeckSF

n	missing	distinct	Info	Mean	Gmd	.05	.10	.25	.50	.75	.90	.95
1460	0	274	0.858	94.24	125	0	0	0	0	168	262	335

lowest : 0 12 24 26 28, highest: 668 670 728 736 857

OpenPorchSF

n	missing	distinct	Info	Mean	Gmd	.05	.10	.25	.50	.75	.90	.95
1460	0	202	0.909	46.66	62.43	0	0	0	25	68	130	175

lowest : 0 4 8 10 11, highest: 406 418 502 523 547

EnclosedPorch

n	missing	distinct	Info	Mean	Gmd	.05	.10	.25	.50	.75	.90	.95
1460	0	120	0.369	21.95	39.39	0.0	0.0	0.0	0.0	0.0	112.0	180.1

lowest : 0 19 20 24 30, highest: 301 318 330 386 552

X3SsnPorch

n	missing	distinct	Info	Mean	Gmd	.05	.10	.25	.50	.75	.90	.95
1460	0	20	0.049	3.41	6.739	0	0	0	0	0	0	0

Value	0	23	96	130	140	144	153	162	168	180	182	196	216	238
Frequency	1436	1	1	1	1	2	1	1	3	2	1	1	2	1
Proportion	0.984	0.001	0.001	0.001	0.001	0.001	0.001	0.001	0.002	0.001	0.001	0.001	0.001	0.001

Value	245	290	304	320	407	508
Frequency	1	1	1	1	1	1
Proportion	0.001	0.001	0.001	0.001	0.001	0.001

ScreenPorch

n	missing	distinct	Info	Mean	Gmd	.05	.10	.25	.50	.75	.90	.95
1460	0	76	0.22	15.06	28.27	0	0	0	0	0	0	160

lowest : 0 40 53 60 63, highest: 385 396 410 440 480

PoolArea

n	missing	distinct	Info	Mean	Gmd
1460	0	8	0.014	2.759	5.497

Value	0	480	512	519	555	576	648	738
Frequency	1453	1	1	1	1	1	1	1
Proportion	0.995	0.001	0.001	0.001	0.001	0.001	0.001	0.001

PoolQC

n	missing	distinct
7	1453	3

Value	Ex	Fa	Gd
Frequency	2	2	3
Proportion	0.286	0.286	0.429

Fence

n	missing	distinct
281	1179	4

Value	GdPrv	GdWo	MnPrv	MnWw
Frequency	59	54	157	11
Proportion	0.210	0.192	0.559	0.039

MiscFeature

n	missing	distinct
54	1406	4

Value	Gar2	Othr	Shed	TenC
Frequency	2	2	49	1
Proportion	0.037	0.037	0.907	0.019

MiscVal

n	missing	distinct	Info	Mean	Gmd	.05	.10	.25	.50	.75	.90	.95
1460	0	21	0.103	43.49	85.67	0	0	0	0	0	0	0

Value	0	50	350	400	450	500	550	600	700	800	1150	1200	1300	1400
Frequency	1408	1	1	11	4	10	1	5	5	1	1	2	1	1
Proportion	0.964	0.001	0.001	0.008	0.003	0.007	0.001	0.003	0.003	0.001	0.001	0.001	0.001	0.001

Value	2000	2500	3500	8300	15500
Frequency	4	1	1	1	1
Proportion	0.003	0.001	0.001	0.001	0.001

MoSold

n	missing	distinct	Info	Mean	Gmd	.05	.10	.25	.50	.75	.90	.95
1460	0	12	0.985	6.322	3.041	2	3	5	6	8	10	11

Value	1	2	3	4	5	6	7	8	9	10	11	12
Frequency	58	52	106	141	204	253	234	122	63	89	79	59
Proportion	0.040	0.036	0.073	0.097	0.140	0.173	0.160	0.084	0.043	0.061	0.054	0.040

YrSold

n	missing	distinct	Info	Mean	Gmd
1460	0	5	0.955	2008	1.498

Value	2006	2007	2008	2009	2010
Frequency	314	329	304	338	175
Proportion	0.215	0.225	0.208	0.232	0.120

SaleType

n	missing	distinct
1460	0	9

Value	COD	Con	ConLD	ConLI	ConLw	CWD	New	Oth	WD
Frequency	43	2	9	5	5	4	122	3	1267
Proportion	0.029	0.001	0.006	0.003	0.003	0.003	0.084	0.002	0.868

SaleCondition

n	missing	distinct
1460	0	6

Value	Abnorml	AdjLand	Alloca	Family	Normal	Partial
Frequency	101	4	12	20	1198	125
Proportion	0.069	0.003	0.008	0.014	0.821	0.086

6.2 Variable Selection

In the previous tables we see a number of variables with `NAs`. For simplicity, we will exclude the columns containing `NAs` and attempt to identify the variables of greatest importance.

6.3 Variable Subset Matrix

```
library(leaps)
train.df.2 <- train.df[ , colSums(is.na(train.df)) == 0]
subsetModel <- suppressMessages(regsubsets(SalePrice ~ ., data = train.df.2,
                          nbest = 1, really.big = T,  method = "seqrep"))
```

```
## Reordering variables and trying again:
```

```
summary <- summary(subsetModel, matrix = TRUE)
kable(t(summary$outmat))
```

	1 (1)	2 (1)	3 (1)	4 (1)	5 (1)	6 (1)	7 (1)	8 (1)	9 (1)
Id									
MSSubClass						*	*	*	*
MSZoningFV									
MSZoningRH									
MSZoningRL									
MSZoningRM									
LotArea									
StreetPave									
LotShapeIR2									
LotShapeIR3									
LotShapeReg									
LandContourHLS									
LandContourLow									
LandContourLvl									
UtilitiesNoSeWa									
LotConfigCulDSac									
LotConfigFR2									
LotConfigFR3									
LotConfigInside									
LandSlopeMod									
LandSlopeSev									
NeighborhoodBlueste									
NeighborhoodBrDale									
NeighborhoodBrkSide									
NeighborhoodClearCr									
NeighborhoodCollgCr									
NeighborhoodCrawfor									
NeighborhoodEdwards									
NeighborhoodGilbert									
NeighborhoodIDOTRR									
NeighborhoodMeadowV									
NeighborhoodMitchel									
NeighborhoodNAmes									
NeighborhoodNoRidge								*	*
NeighborhoodNPkVill									
NeighborhoodNridgHt					*	*	*	*	*
NeighborhoodNWAmes									
NeighborhoodOldTown									
NeighborhoodSawyer									
NeighborhoodSawyerW									
NeighborhoodSomerst									
NeighborhoodStoneBr							*	*	*
NeighborhoodSWISU									
NeighborhoodTimber									
NeighborhoodVeenker									
Condition1Feedr									

	1 (1)	2 (1)	3 (1)	4 (1)	5 (1)	6 (1)	7 (1)	8 (1)	9 (1)
Condition1Norm									
Condition1PosA									
Condition1PosN									
Condition1RRAe									
Condition1RRAn									
Condition1RRNe									
Condition1RRNn									
Condition2Feedr									
Condition2Norm									
Condition2PosA									
Condition2PosN									
Condition2RRAe									
Condition2RRAn									
Condition2RRNn									
BldgType2fmCon									
BldgTypeDuplex									
BldgTypeTwnhs									
BldgTypeTwnhsE									
HouseStyle1.5Unf									
HouseStyle1Story									
HouseStyle2.5Fin									
HouseStyle2.5Unf									
HouseStyle2Story									
HouseStyleSFoyer									
HouseStyleSLvl									
OverallQual	*	*	*	*	*	*	*	*	*
OverallCond									
YearBuilt						*	*	*	
YearRemodAdd									*
RoofStyleGable									
RoofStyleGambrel									
RoofStyleHip									
RoofStyleMansard									
RoofStyleShed									
RoofMatlCompShg									
RoofMatlMembran									
RoofMatlMetal									
RoofMatlRoll									
RoofMatlTar&Grv									
RoofMatlWdShake									
RoofMatlWdShngl									
Exterior1stAsphShn									
Exterior1stBrkComm									
Exterior1stBrkFace									
Exterior1stCBlock									
Exterior1stCemntBd									
Exterior1stHdBoard									
Exterior1stImStucc									
Exterior1stMetalSd									
Exterior1stPlywood									
Exterior1stStone									
Exterior1stStucco									
Exterior1stVinylSd									
Exterior1stWd Sdng									
Exterior1stWdShing									
Exterior2ndAsphShn									
Exterior2ndBrk Cmn									
Exterior2ndBrkFace									
Exterior2ndCBlock									
Exterior2ndCmentBd									
Exterior2ndHdBoard									
Exterior2ndImStucc									
Exterior2ndMetalSd									
Exterior2ndOther									
Exterior2ndPlywood									
Exterior2ndStone									

	1 (1)	2 (1)	3 (1)	4 (1)	5 (1)	6 (1)	7 (1)	8 (1)	9 (1)
Exterior2ndStucco									
Exterior2ndVinylSd									
Exterior2ndWd Sdng									
Exterior2ndWd Shng									
ExterQualFa									
ExterQualGd									
ExterQualTA									
ExterCondFa									
ExterCondGd									
ExterCondPo									
ExterCondTA									
FoundationCBlock									
FoundationPConc									
FoundationSlab									
FoundationStone									
FoundationWood									
BsmtFinSF1			*	*	*	*	*	*	*
BsmtFinSF2									
BsmtUnfSF									
TotalBsmtSF									
HeatingGasA									
HeatingGasW									
HeatingGrav									
HeatingOthW									
HeatingWall									
HeatingQCFa									
HeatingQCGd									
HeatingQCPo									
HeatingQCTA									
CentralAirY									
X1stFlrSF									
X2ndFlrSF									
LowQualFinSF									
GrLivArea		*	*	*	*	*	*	*	*
BsmtFullBath									
BsmtHalfBath									
FullBath									
HalfBath									
BedroomAbvGr									
KitchenAbvGr									
KitchenQualFa									
KitchenQualGd									
KitchenQualTA									
TotRmsAbvGrd									
FunctionalMaj2									
FunctionalMin1									
FunctionalMin2									
FunctionalMod									
FunctionalSev									
FunctionalTyp									
Fireplaces									
GarageCars				*	*				*
GarageArea									
PavedDriveP									
PavedDriveY									
WoodDeckSF									
OpenPorchSF									
EnclosedPorch									
X3SsnPorch									
ScreenPorch									
PoolArea									
MiscVal									
MoSold									
YrSold									
SaleTypeCon									
SaleTypeConLD									

	1 (1)	2 (1)	3 (1)	4 (1)	5 (1)	6 (1)	7 (1)	8 (1)	9 (1)
SaleTypeConLI									
SaleTypeConLw									
SaleTypeCWD									
SaleTypeNew									
SaleTypeOth									
SaleTypeWD									
SaleConditionAdjLand									
SaleConditionAlloca									
SaleConditionFamily									
SaleConditionNormal									
SaleConditionPartial									

6.4 First Model

Based on the last best model we will limit the data set to the following variables `MSSubClass`, `NeighborhoodNoRidge`, `NeighborhoodNridgHt`, `NeighborhoodStoneBr`, `OverallQual`, `YearRemodAdd`, `BsmtFinSF1`, `GrLivArea`, `GarageCars`.

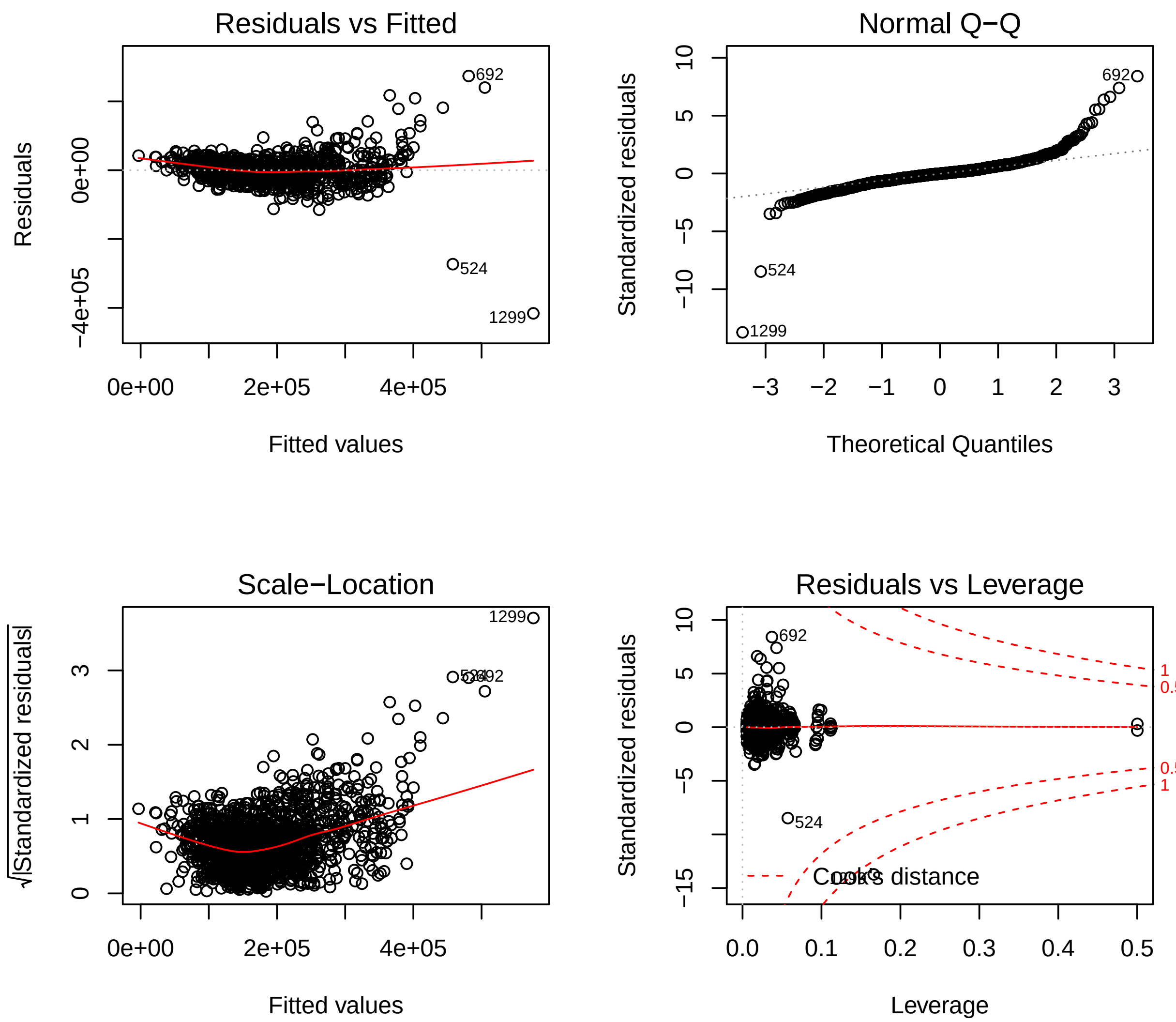
```
fit <- lm(SalePrice ~ MSSubClass + Neighborhood +
            OverallQual + YearRemodAdd + BsmtFinSF1 +
            GrLivArea + GarageCars, data = train.df)

stargazer(fit, header = FALSE, no.space = TRUE,
          style = "all2", font.size = "footnotesize",
          single.row = TRUE, intercept.bottom = FALSE)
```

Table 7:

	Dependent variable:
	SalePrice
Constant	−621,777.700*** (111,442.300)
MSSubClass	−252.678*** (24.405)
NeighborhoodBlueste	−12,510.880 (24,882.880)
NeighborhoodBrDale	−16,417.030 (11,866.240)
NeighborhoodBrkSide	−14,640.440 (9,753.068)
NeighborhoodClearCr	7,771.633 (10,647.930)
NeighborhoodCollgCr	−8,855.995 (8,742.258)
NeighborhoodCrawfor	7,447.104 (9,729.488)
NeighborhoodEdwards	−24,629.000*** (9,317.138)
NeighborhoodGilbert	−12,303.590 (9,065.933)
NeighborhoodIDOTRR	−25,820.490** (10,379.870)
NeighborhoodMeadowV	1,205.989 (11,879.710)
NeighborhoodMitchel	−18,072.460* (9,692.696)
NeighborhoodNAmes	−18,834.730** (8,971.063)
NeighborhoodNoRidge	40,530.480*** (10,050.780)
NeighborhoodNPkVill	−9,409.847 (13,823.590)
NeighborhoodNridgHt	49,514.520*** (9,100.426)
NeighborhoodNWAmes	−21,429.510** (9,344.861)
NeighborhoodOldTown	−31,650.010*** (9,111.020)
NeighborhoodSawyer	−19,047.140** (9,502.205)
NeighborhoodSawyerW	−15,759.290* (9,404.611)
NeighborhoodSomerst	7,011.384 (8,880.182)
NeighborhoodStoneBr	55,104.420*** (10,602.380)
NeighborhoodSWISU	−27,693.620** (11,081.320)
NeighborhoodTimber	3,500.186 (9,974.428)
NeighborhoodVeenker	25,505.000* (13,027.270)
OverallQual	16,039.450*** (1,094.370)
YearRemodAdd	310.102*** (56.246)
BsmtFinSF1	23.326*** (2.113)
GrLivArea	52.970*** (2.326)
GarageCars	11,974.750*** (1,614.394)
Observations	1,460
R^2	0.829
Adjusted R^2	0.826
Residual Std. Error	33,181.540 (df = 1429)
F Statistic	231.137*** (df = 30; 1429) (p = 0.000)
Note:	*p<0.1; **p<0.05; ***p<0.01

6.4.1 Diagnostic Plots

```r
p <- par(mfrow=c(2,2))
plot(fit)
```



The residual plot does not look like a shotgun pattern and we may be violating the assumption of random variance. My assumption is that the high influence points and/or outliers may be impacting the model. Therefore, we will exclude the high influence points from our final model. We will also take the log of SalePrice as we began to get negative predictions after removing the high influence points.

6.5 Final Model

```
train.df.2 <- train.df[-c(524, 1299),]
fit <- lm(I(log(SalePrice)) ~ MSSubClass + Neighborhood +
            OverallQual + YearRemodAdd + BsmtFinSF1 +
            GrLivArea + GarageCars, data = train.df.2)
```

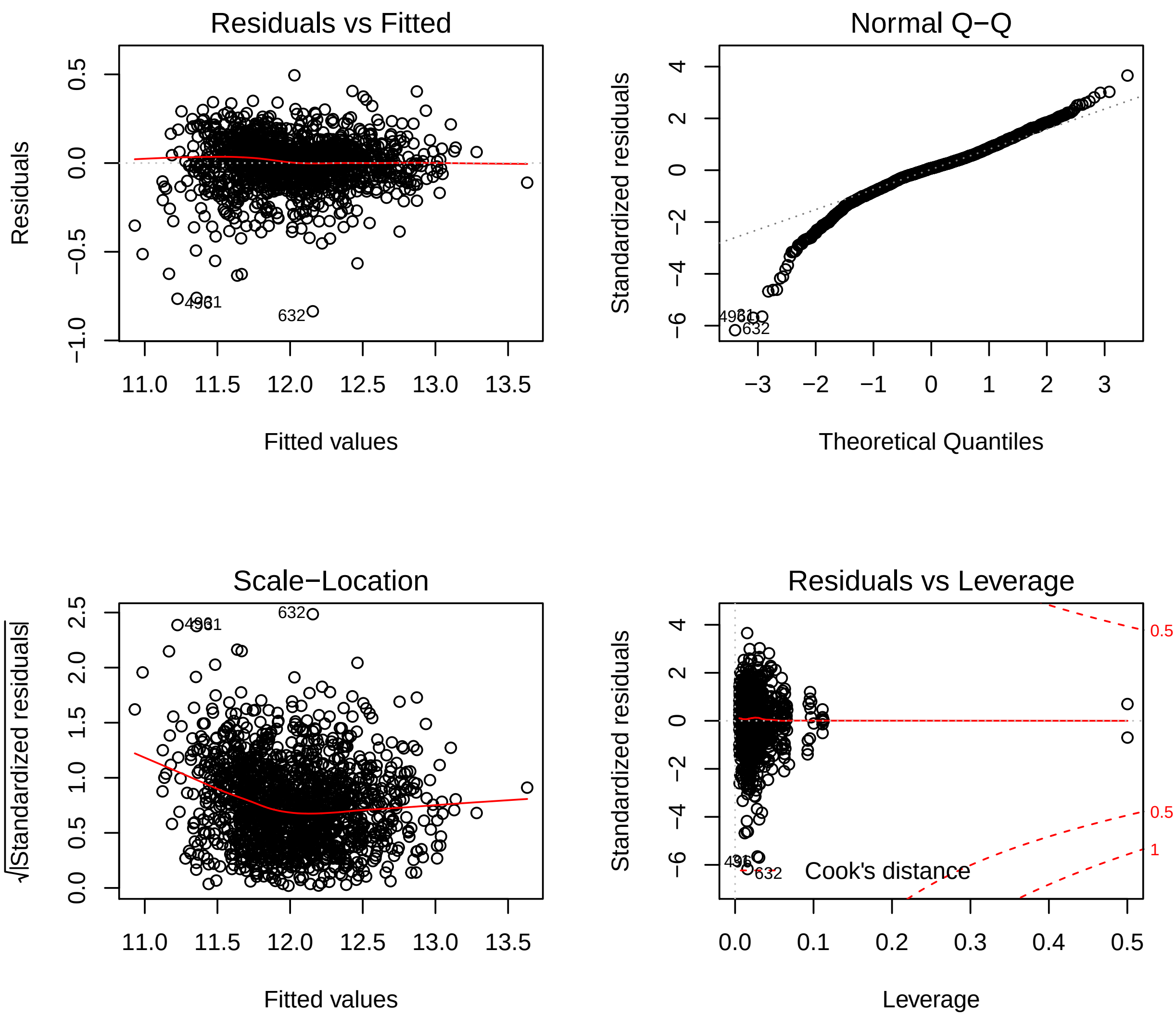
Table 8: Final Model

	Dependent variable:
	I(log(SalePrice))
Constant	5.914*** (0.458)
MSSubClass	−0.001*** (0.0001)
NeighborhoodBlueste	−0.096 (0.102)
NeighborhoodBrDale	−0.209*** (0.049)
NeighborhoodBrkSide	−0.110*** (0.040)
NeighborhoodClearCr	0.067 (0.044)
NeighborhoodCollgCr	−0.029 (0.036)
NeighborhoodCrawfor	0.046 (0.040)
NeighborhoodEdwards	−0.126*** (0.038)
NeighborhoodGilbert	−0.030 (0.037)
NeighborhoodIDOTRR	−0.265*** (0.043)
NeighborhoodMeadowV	−0.157*** (0.049)
NeighborhoodMitchel	−0.078* (0.040)
NeighborhoodNAmes	−0.064* (0.037)
NeighborhoodNoRidge	−0.012 (0.042)
NeighborhoodNPkVill	−0.061 (0.057)
NeighborhoodNridgHt	0.072* (0.038)
NeighborhoodNWAmes	−0.067* (0.038)
NeighborhoodOldTown	−0.212*** (0.037)
NeighborhoodSawyer	−0.079** (0.039)
NeighborhoodSawyerW	−0.078** (0.039)
NeighborhoodSomerst	0.019 (0.037)
NeighborhoodStoneBr	0.093** (0.044)
NeighborhoodSWISU	−0.131*** (0.046)
NeighborhoodTimber	−0.004 (0.041)
NeighborhoodVeenker	0.105** (0.054)
OverallQual	0.091*** (0.005)
YearRemodAdd	0.003*** (0.0002)
BsmtFinSF1	0.0002*** (0.00001)
GrLivArea	0.0003*** (0.00001)
GarageCars	0.069*** (0.007)
Observations	1,457
R^2	0.885
Adjusted R^2	0.882
Residual Std. Error	0.136 (df = 1426)
F Statistic	365.465*** (df = 30; 1426) (p = 0.000)
Note:	*p<0.1; **p<0.05; ***p<0.01

There are some interesting coeffecients in our final model. It is unsurprising that we see certain neighboorhoods have greater impact to the sale price but it is interesting to see the specific ones. I am also surprised that the number of cars that a garage can hold has such a great impact. Intuitively, it makes sense that more cars indicates greater wealth and a higher sale price but it was expected to see it represented in our model.

6.5.1 Diagnostic Plots

```
fit.plot <- lm(log(SalePrice) ~ MSSubClass + Neighborhood +
             OverallQual + YearRemodAdd + BsmtFinSF1 +
             GrLivArea + GarageCars, data = train.df.2)
p <- par(mfrow=c(2,2))
plot(fit.plot)
```



Now we see a more random variance in our diagnostic plots and I am more comfortable with our model. Taking the log of our outcome variable has improved our ability to validate this model.

6.5.2 Multicollinearity

```
library(car)
library(data.table)
rmfit <- setDT(as.data.frame(car::vif(fit)), keep.rownames = TRUE)[]
rmfit$Adjusted_GVIF <- (rmfit$`GVIF^(1/(2*Df))`^2)
kable(rmfit, align = c("l", "c", "c", "c", "c"))
```

rn	GVIF	Df	GVIF^(1/(2*Df))	Adjusted_GVIF
MSSubClass	1.413403	1	1.188866	1.413403
Neighborhood	5.812676	24	1.037348	1.076091
OverallQual	2.988764	1	1.728804	2.988764
YearRemodAdd	1.784746	1	1.335944	1.784746
BsmtFinSF1	1.238327	1	1.112801	1.238327
GrLivArea	1.968825	1	1.403148	1.968825
GarageCars	1.936513	1	1.391587	1.936513

Using GVIF^(1/(2*Df)) [4] in order to verify that the VIF threshold of 5 for multicollinearity is not exceed. Fortunately, we find that no variable exceeds the threshold and we do not need to adjust for multicollinearity.

6.6 Prediction results with test data set using final model

First there are some observations that are missing values included in our model. For this reason, we will use imputation to complete the cases so our predictions can be carried out.

```
test.df  <- as_tibble(read.csv(paste("https://raw.githubusercontent.com/",
                                     "ChristopheHunt/",
                                      "MSDA---Coursework/master",
                                      "/Data%20605/Final%20Project/test.csv",
                                     sep = "")))
```

6.6.1 Imputation

The test data provided by Kaggle has `NAs` for some of our independent variables. As such, we will use a non-parametic method of imputation so that we can run our final model.

```
library(missForest)
registerDoParallel(cl = makeCluster(8), cores = 8)
set.seed(1234)
test.df.imp <- as.data.frame(test.df %>% dplyr::select(Id, MSSubClass, Neighborhood,
                                                       OverallQual, OverallCond,
                                                       YearBuilt, YrSold,
                                                       YearRemodAdd, BsmtFinSF1,
                                                       GrLivArea,GarageCars)) %>%
  missForest(maxiter = 10, ntree = 100,
             replace = TRUE, parallelize = 'forests', verbose = TRUE)

write.csv(test.df.imp$ximp,"imputed_test_data.csv", row.names = FALSE)
#imputed_data to csv file due to processing time taken by missForest
```

[4] "Which Variance Inflation Factor Should I Be Using: $GVIF$ or $textGVIF^{1/(2cdottextdf)}$?" R. N.p., n.d. Web. 13 Nov. 2016.

6.7 Prediction results

```
test.df  <- as_tibble(read.csv(paste("https://raw.githubusercontent.com/",
                                      "ChristopheHunt/",
                                       "MSDA---Coursework/master",
                                       "/Data%20605/Final%20Project/imputed_test_data.csv",
                                      sep = "")))

SalePrice.predict <- exp(predict.lm(fit, type = "response", newdata = test.df))
test.df.wpredict <- cbind(test.df %>% dplyr::select(Id), round(SalePrice.predict,0))
colnames(test.df.wpredict)[2] <- c("SalePrice")
kable(head(test.df.wpredict), split.table = Inf)
```

Id	SalePrice
1461	116767
1462	153700
1463	177987
1464	188130
1465	207117
1466	172621

6.7.1 Prediction results for submission

```
gz1 <- gzfile("submission.csv.gz", "w")
write.csv(test.df.wpredict, gz1, row.names = FALSE)
close(gz1)
```

6.8 Kaggle Results

Kaggle.com user name: `Blastophe`

Kaggle.com score: `0.15033`